1. Title of the Thesis: Exploration of Soft Computing Approaches in Temporal Itemset Utility Mining

2. Introduction :

With the development of technology, the difficulty to obtain data is decreasing and the difficulty to analyse the huge volume of data is increasing. That is to say, it is technically more difficult to extract knowledge from the huge volume of data, which are currently being stored in databases. All these have prompted the need for intelligent data analysis methodologies, which could discover useful knowledge from data

As mentioned in [SSP02], KDD focuses on the overall process of knowledge discovery from large volumes of data, including the storage and accessing of such data, scaling of algorithms to massive data sets, interpretation and visualization of results and the modeling and support of the overall human machine interaction.

Data mining is a step in the KDD process consisting of a particular enumeration of patterns over the data, subject to some computational limitations. The data can consist of a collection of time series descriptions that can be learned to predict later events in the series.

An important area of data mining research deals with the discovery of association rules. The mining of Association rules for finding the relationships between data items in large datasets is a well studied technique in the data mining field with representative methods like Apriori **[RTA93].**

The basic Bottleneck of association rule mining is Rare Item Problem. Most approaches to mining association rules implicitly consider the utilities of the itemsets to be equal**[YHB04].** The utilities of itemsets may differ. Standard methods for mining association rules **[RTA93]** are based on the *support–confidence model*. First find all *frequent itemsets* with support of at least *minsup* and then generate all association rules with confidence of at least *minconf*. The frequency of an itemset may not be a sufficient indicator of interestingness because it does not reveal the *utility* of an itemset, which can be measured in terms of cost, profit, or other expressions of user preference. In many applications, some items appear very frequently in the data, while others rarely appear.

If frequencies of items vary, two problems encountered –(1) If minsup is set too high, then rules of rare items will not be found (2) To find rules that involve both frequent and rare items, minsup has to be set very low. This may cause combinatorial explosion.

Another problem that arise during the data mining process is treating data that contains temporal information. Temporal association rule mining is to discover the valuable relationship among the items in the temporal database **[ZTLJ05].** This incorporation is especially necessary if we want to extract useful knowledge from dynamic domains, which are timevarying in nature. However, in a lot of cases is practically a computationally intractable problem and therefore it poses more challenges on efficient processing than non-temporal techniques.

Soft computing is a consortium of methodologies that works synergistically and provides, in one form or another, flexible information processing capability for handling real-life ambiguous situations **[SSP02].** Its aim is to exploit the tolerance for imprecision, uncertainty, approximate reasoning, and partial truth in order to achieve tractability, robustness, and low-cost solutions.

Soft computing methodologies (involving fuzzy sets, neural networks, genetic algorithms, and rough sets) are most widely applied in data mining. The modeling of imprecise and qualitative knowledge, as well as the transmission and handling of uncertainty at various stages are possible through the use of fuzzy sets. Fuzzy logic is capable of supporting, to a reasonable extent, human type reasoning in natural form **[SSP02].** In the theoretical framework of Soft Computing, the problem of machine intelligence can be tackled by combining unconventional approaches that have profoundly improved the situation.

In many applications, for example-market or data streams, use of discrete valued utilities alone is inadequate. In many cases where values are uncertain, a fuzzy representation may be more appropriate. Most utility items are linked with temporal constraints i.e. an itemsets utility is a temporal feature that may vary over a given time period. The utility value itself can be discrete or fuzzy and thus demands a new theoretic approach to the problem.

Temporal Itemset Utility Mining with fuzzy approach allows item utility values to be dynamic over time and assumes fuzzy values. This approach allows development of an efficient and applicable algorithm that captures real-life situations in ARM.

3. Brief Review of work already done in the field:

Sushmita Mitra et al provides a survey on data mining using soft computing **[SSP2].** A categorization has been provided based on the different soft computing tools and their hybridizations used, the data mining function implemented, and the preference criterion selected by the model. The utility of the different soft computing methodologies is highlighted. Generally fuzzy sets are suitable for handling the issues related to understandability of patterns, incomplete/noisy data, mixed media information and human interaction, and can provide approximate solutions faster. Neural networks are nonparametric, robust, and exhibit good learning and generalization capabilities in data-rich environments. Genetic algorithms provide efficient search algorithms to select a model, from mixed media data, based on some preference criterion/objective function. Rough sets are suitable for handling different types of uncertainty in data.

Ashish Mangalampalli et al. in **[AV06],** describes in detail, a methodology to do the pre-processing which first involves using fuzzy clustering to generate fuzzy partitions and then use these partitions to get a fuzzy version (with fuzzy records) of the original dataset. Ultimately, the fuzzy data (fuzzy records) are represented in a standard manner such that they can be used as input to any kind of fuzzy ARM algorithm, irrespective of how it works and processes the fuzzy data. And finally, it shows how existing algorithms, like Apriori, ARMOR, and FPGrowth can be modified.

In **[JW06], Junheng-Huang et al.,** explored a new mode of mining general temporal association rules from large databases where the exhibition periods of the items are allowed to be different from one to another. An efficient algorithm, referred to as SPFA (Standing for Segmented Progressive Filter Algorithm) is described to discover general temporal association rules effectively. The experimental results showed that SPFA significantly outperforms other schemes, which are extended from prior methods in terms of the execution time and scalability.

Francisco Guil1 et al., presented and evaluated ***TSET Algorithm*[FAR04]**, which uses a tree-based data structure to discover frequent sequences (intertransactional associations) from datasets. Although the use of a unique structure causes that the algorithm requires less memory than other approaches, mining this type of associations is still a computationally intensive problem.

Zhai Liang et al. have presented **[ZTLJ05]** and discussed the problems of temporal association rule mining based on a sequence of ecological events.

In **[YPXS03], Yingjiu Li et al.**, proposed two classes of temporal association rules, temporal association rules w.r.t. precise match and temporal association rules w.r.t. fuzzy match, to represent regular association rules along with their temporal patterns in terms of calendar schemas.

4. Note worthy contribution:

Keshri Verma et al. have proposed algorithm H-mine, in **[KO05],** which takes advantage of H-struct data structure and dynamically adjust link in the mining process. This algorithm gives an efficient time sensitive approach for mining frequent item in the dataset. This approach reduces the size of dataset and increases the performance & efficiency of algorithm. Temporal FP-tree, uses divide & conquer technique for construction & traversing of tree, which is used to decompose the mining task into a set of smaller tasks for mining confined pattern in conditional database which reduce the search space on specific time interval when the data is sparse **[KO05].**

Ranjana Vyas et al, have proposed Temporal data mining, implemented and compared on performance issues such as temporal dimension in existing Associative Classifiers CBA, CMAR AND CPAR. In **[RVON08],** conclusion is that Temporal Associative Classifier performs better in terms of classifier accuracy as compared to their non-temporal counterparts.

Maybin Muyeba in **[MM09],** presents a new foundational approach to itemset utility mining where item utility values are allowed to be dynamic over time and can also assume fuzzy values on the other hand. A Theoretical model has been presented that

allows development of an efficient and applicable algorithm that captures real-life situations in association rule mining **[MM09].** The approach also shows validation of downward closure property, which is difficult in utility mining.

Chu, C.-J. et al proposed a Novel method, namely **THUI (Temporal High Utility Itemsets)- Mine**, for mining temporal high utility itemsets from data streams efficiently and effectively. The Novel contribution of THUI-Mine is that it can effectively identify the temporal high utility itemsets by generating fewer candidate itemsets such that the execution time can be reduced substantially in mining all high utility itemsets in data streams. In this way, the process of discovering all temporal high utility itemsets under all time windows of data streams can be achieved effectively with less memory space and execution time.

In **[YWA05], Ying Liu et al**. present a Two-Phase algorithm to efficiently prune down the number of candidates and precisely obtain the complete set of high utility itemsets. It performs very efficiently in terms of speed and memory cost both on synthetic and real databases, even on large databases that are difficult for existing algorithms to handle.

In **[KCA96], Keith C. et al.**, introduce a novel algorithm called APACS2, which has several unique features: (i) it is able to avoid the use of some user-supplied threshold to define the interestingness of the associations and (ii) discover both positive and negative associations.

5. Proposed methodology during the tenure of research work :

During the last ten years, data mining, also known as knowledge discovery in databases has established its position as a prominent and important research area. The goal of data mining is to extract higher-level information from an abundance of raw data (AG00).

Mining Association rules is one of the research problems in data mining (RTA93). Given a set of transactions where each transaction is a set of items, an association rule is an expression of the form $X \Rightarrow Y$, where X and Y are sets of items.

The problem of mining association rules was first introduced in (RTA93) and later broadened in (RR94), for the case of databases consisting of categorical attributes alone.

Association rule mining (ARM) is a popular technique for finding co-occurrences of items in a set of transactions or a database. Rules with confidence and support above user-defined thresholds (minconf and minsup) were found. As data continues to grow and its complexity increases, newer data structures and algorithms are being developed to match this development.

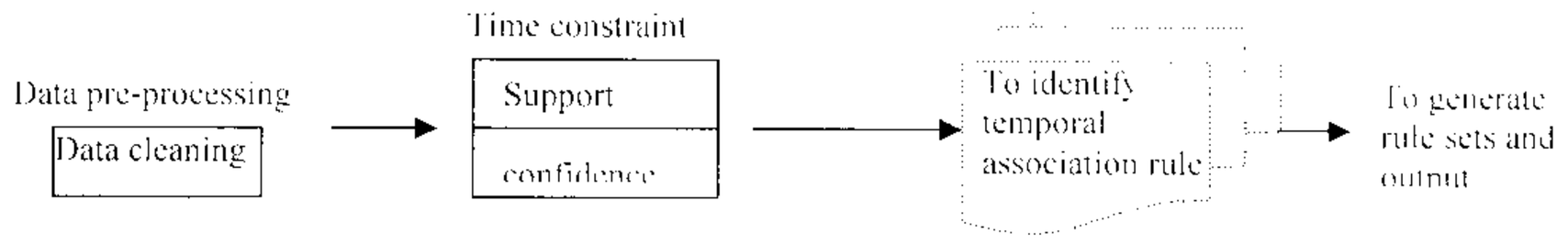
Almost all Association rule mining algorithms treat each itemset to be of equal value (or importance) and only use support and confidence heuristics to measure rule quality. In real life applications, an itemset can be valued more highly, not only because of its frequency, but also of its importance or utility. Most utility items are linked with temporal constraints i.e. an itemsets utility is a temporal feature that may vary over a given time period. The utility value itself can be discrete or fuzzy and thus demands a new approach to the problem**[MM09]**.

An important research issue extended from the mining of association rules is the discovery of temporal association patterns in data streams due to the wide applications in various domains. Temporal Data Mining can be defined as the activity of discovering interesting correlations or patterns in large data sets of temporal data accumulated for other purposes. For time-variant data streams, there is a strong demand to develop an efficient and effective method to mine various temporal patterns. However, most methods designed for traditional databases cannot be directly applied to the mining of temporal patterns in data streams because of their high complexity.

Temporal Association rule adds time constraint on association rule. The definition of strong temporal association rule is : Let min_s and min_c represent minimum support and confidence threshold respectively, if and only if during $[t_s, t_e]$, support >= min_s, confidence >= min_c, rule $X \Rightarrow Y$ is a temporal association rule, which could be described as $X \Rightarrow Y$(support, confidence, $[t_s, t_e]$).

Temporal Association Rule Mining can be divided into 4 steps: **[ZTLJ05]**

(1) Data preprocessing. It includes data cleaning, data integration, data exchange and data reduction.
(2) To find frequent itemsets which have the support not less than min_sup.
(3) To generate association rules with frequent itemsets with time. The rules generated are temporal ones.
(4) To generate rule sets and output.



Almost all Association rule mining algorithms treat each itemset to be of equal value (or importance) and only use support and confidence heuristics to measure rule quality. In real life applications, an itemset can be valued more highly, not only because of its frequency, but also of its importance or utility.

Utility mining aims at identifying the itemsets with high utilities. The temporal high utility itemsets are the itemsets which appear infrequently in current time window of large databases but whose support is larger than a pre-specified threshold in current time window of the data stream. Discovery of temporal high utility itemsets is an important process of mining interesting patterns like association rules from data streams **[CVT07].**

Utility Mining gives additional constraints to items to help generate rules with sufficient conditions such as revealing the utility of an itemset and thus help generate more informed association rule. For example, low support itemsets may be more profitable than high support itemsets and hence pruning techniques in normal association rule mining may miss such items.

Utility values should be allowed to have continuous or fuzzy values. For example, for stock exchange data, share prices of one particular product may remain constant; in same period of time other product's share price changes ten times. Utility Mining frameworks ought to reflect such dynamicity within time partitions being considered.

Soft computing was first proposed by Zadeh (1998), to construct new generation computationally intelligent hybrid systems consisting of neural networks, fuzzy inference system, approximate reasoning and derivative free optimization techniques. Recently various soft computing methodologies have been applied to handle the different challenges posed by data mining. Fuzzy provides a remarkably simple way to draw definite conclusions from vague, ambiguous or imprecise information and resembles human decision-making. Fuzzy ARM is still in its nascent stage, even though very good research has been done in this field.

Definition 1: Utility Mining is defined in **[YHB04]** by Hong Yao et al, as - Let $I = \{i1, i2, \ldots im\}$ be a set of items, D be a transaction database, and UT<I, U> be a utility table, where U is a subset of the real numbers that reflect the utilities of the items. The *utility mining problem* is to discover all itemsets in a transaction database D with utility values higher than the *minutil* threshold, given a utility table UT.

Definition 2:**[MM09]** A utility table UT is a triple $UT =< I, U, P >$ where each i has some utility value u_j in $U = \{u_1, u_2, u_3, .., u_{|k|}\}$ for some $k > 0$. These utility values are set accordingly and correspond to a given set of time granularities $T_{u_j} = \{t_1, t_2, .., t_k\}, k > 0$ i.e. u_j corresponds to t_j.

T_u=1 T_u =2 ----------

ITEM	Utility TID		
	T1	T2	T3
A	{L,M,H}	{VL,L,M}	{L,H,H}
B	{M,M,H}	{VL,M,H}	{L,M,H}
C	{L,H,M}	{L,M,H}	{M,M,H}

ITEM	Utility TID		
	T1	T2	T3
A	{L,M,M}	{L,M,H}	{L,M,H}
B	{M,M,H}	{VL,L,M}	{L,M,H}
C	{L,L,M}	{L,M,H}	{M,M,H}

Figure1: Temporal Utility table having Fuzzy values within transactions periods.

For example- Consider a database(table 1) with time granularities (P1, P2, P3, P4). Table 2 shows that if we had four time periods (P1, P2, P3, P4), for example first, second, third and fourth quarters, each of the items' values would be variable. This is typical naturally for particular times of the year (or seasons) where some items become more in demand, profitability etc than others. In period 2, the best utility item is A with 5, followed by B and then C, but in period 3, item B has the highest utility of 10 etc.

In transaction 1 [table 2], item C with quantity 50 has utility 2 in period 1 (C, 2, 1)=50 (table 2 item C) and its utility in transaction T1 is 50*2=100. For period 1, item C's utility is 50*2+12*2+25*2=174. In comparison, item C's utility for period 2 is 3*1+3*1+4*1=10, which reflects a remarkable difference.

Table 1. Transaction Database

	TID	*A*	*B*	*C*
P1	**1**	20	5	50
	2	10	4	12
	3	8	0	25
P2	**4**	1	2	3
	5	6	4	3
	6	13	2	4
P3	7	5	10	2
	8	3	5	1
P4	9	1	3	2
	10	30	50	5
	11	3	12	15

Table 2. Temporal utility table (Year quarters)

Item	U	T_u
A	{4, 5, 4, 15}	{<t1>, <t2>, <t3>, <t4>}
B	{7, 4, 10, 2}	{<t1>, <t2>, <t3>, <t4>}
C	{2, 1, 5, 8}	{<t1>, <t2>, <t3>, <t4>}

Let Dataset Z have transactions T= $\{t_1, t_2, \ldots, t_n\}$ and X is set of items X= $\{ x_1, x_2, \ldots, x_n \}$. P= $\{P_1, P_2, \ldots, P_k\}$ is a set of time granularities.

Definition 3: **[MM09] Utility Temporal Support** is sum of the utilities of the item, presented in all transactions, divided by the total number of transactions in a particular time period. It is formulated as:

$$UTS(x_i) = \frac{\sum_{q=1,\ x_i \in t_q \wedge U \wedge X,\ t_q \in P_k}^{n} (Z.t_q.x_i * U.t_q.x_i)}{\sum_{q=1,\ t_q \in P_k} (t_q)}$$

Definition 4: **Utility Temporal Confidence [MM09]** is the ratio of sum of votes satisfying both AUB to the sum of votes satisfying A. It is formulated as:

UTC (A → B) = UTS (A U B) / UTS (A) = UTS (A) + UTS (B) / UTS (A)

A fuzzy utility value can also be defined in contrast to the discrete utility values given in table 1. The motivation for this approach is that it is not always possible to precisely define a utility value for an item but allowing a range of values in which these values occur is also practical and applicable. For example, item A can have fuzzy values {Low, High, Medium, Low} corresponding to the time periods and represented by some fuzzy membership function. Each item can be assumed to have a different set of fuzzy sets describing utilities.

1. The proposed work will present a new foundational approach to itemset utility mining where item utility values are allowed to be dynamic over time and can also assume fuzzy values on the other hand.
2. This is a generalization of the association rule mining problem. In this generalization, the items are assigned utilities to reflect their importance.
3. The proposed work will develop an algorithm, which aims at identifying itemsets with highest utilities.
4. Most utility items are linked with temporal constraints and utility value can be discrete or fuzzy. The new algorithm will present a foundation on rare itemset utility mining with fuzzy and temporal features.
5. The proposed new algorithm will be compared with other algorithms using benchmark data.

6. Expected Outcome of the proposed research work:

1. The proposed work will develop an algorithm using Temporal Itemset Utility Mining along with Fuzzy approach.
2. The proposed algorithm will deal with large and dense datasets in an efficient way.
3. Fuzzy sets provide efficient granulation of feature space.
4. Rules generated by new algorithm will be superior to other related methods in terms of accuracy, coverage, fidelity, confusion, size and certainty.
5. The new algorithm will discover the temporal rare utility itemsets with higher performance and less candidate itemsets compared to other algorithms.
6. The proposed work is more realistic in real applications because not all utilities may remain same in a given time partition.

7. List of Publications :

1) Jyothi Pillai, Sunita Soni, O.P.Vyas, ***The Predictive Analytics using Innovative Data Mining approach***, (accepted) in the **I[st] International Conference on Advanced data Analysis, Business Analytics and Intelligence, IIM, Ahmedabad** to be held on 6[th]-7[th] June'09.

2) Jyothi Pillai, Sunita Soni, ***Multi-Relational Classifiers: A survey***. **Proceedings of Colloquium on Mobile Communication and Data and Knowledge Engineering, SOS in Computer Science and IT, Pt. R.S.S.U., Raipur,** 2[nd] -3[rd] , Jan.'09.

3) Jyothi Pillai. Sunita Soni. ***Case Representation and Retrieval in Weight Management Counseling to obese children: A Semi-Fuzzy Approach***. Proceedings of **National Conference on Managing Complexity in Informative World, BITCON'08, BIT, Durg,** 7[th]-8[th] Nov.'08.

4) Jyothi Pillai, Pooja, ***A Case Based Framework for Counseling of Malnutrition problem***. **Proceedings of National Conference on, BITCON'08, BIT, Durg,** 7[th]-8[th] Nov.'08.

5) Pillai J., Soni S., *Usage of Nearest Neighborhood, Decision Tree and Bayesian Classification Techniques in Development of Weight Management Counseling System*, Proceedings of **International Conference on Emerging Trends in Engineering and Technology-ICETET'08, G.H.Raisoni College, Nagpur on** 16[th] – 18[th] July 2008 and **IEEE-Xplore, IEEE Computer Society On-line store, IEEE Computer Society(CSDL) Digital Libraries, IEE INSPEC, EI(Compendex), Thomson ISI**.

6) Jyothi Pillai, Sunita Soni, *An Expert Case-Based System using Decision Tree Induction for Weight Management Counseling To Obese Children*, **International Journal of Computer Science and Applications,IJCSA**, Vol. 1, No. 2, 2008 and Proceedings of **International Conference on Advanced Computing, ICAC'08**.

7) Jyothi Pillai, Sunita Soni, *A Case-Based System using Naive Bayesian Classification for Treatment of Pediatric Obesity*, Proceedings of **National Conference on Information Security : Practices and Challenges, ISAC'08**, 9[th]-10[th] Feb.'08.

8) Jyothi Pillai, Sunita Soni, *A Case-Based Expert System For Weight Management Counseling To Obese Children*, Proceedings of **International Conference on Resource Utilization & Intelligent Systems, INCRUIS'08, Kongu Engineering College, Erode,** 3rd- 5th Jan.'08.

9) Jyothi Pillai, Sunita Soni, *Weight Management Counseling Framework for Obese Children*, Proceedings of **National Conference on Technological Advancements in Processing and Decision Making, BITCON'07, BIT, Durg,** on 16th -17th Mar.'07.

8. Bibliography :

[RTA93] R.Agrawal, T.Imielinski, and A.Swami, "*Mining association rules between sets of items in large databases*", Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data, Washington, pages 207–216, 1993.

[**RR94**] R. Agrawal and R. Srikant, *Fast algorithms for mining association rules*. In VLDB'94, pp. 487-499, Santiago, Chile, Sept., 1994.

[**KCA96**] Keith C. C. Chan Wai-Ho Au, *An Effective Algorithm For Mining Interesting Quantitative Association Rules*, the ACM SIGMOD Int'l Conf. on Management of Data, Montreal, Canada, pp. 1-12, June, 1996.

[**AS97**] Alex Berson, Stephen J. Smith, a book on "*Data Warehousing, Data Mining and OLAP*", Tata Mcgraw Hill Publishing Company Limited, 1997.

[**JR99**] John Yen, Reza Langari, a book on "*Fuzzy Logic: Intelligence, Control and Information*", Pearson education, 1999.

[**AG00**] Attila Gyenesei, *Mining Weighted Association Rules for Fuzzy Quantitative Items*, Lecture notes in Computer Science, Springer, Vol. 1910/2000, pages 187-219, TUCS Technical Report No.346, ISBN 952-12-659-4.ISSN 1239-1891, May 2000.

[**JM01**] Jiawei Han, Micheline Kamber, Book:"*Data Mining Concept & Technique*", Morgan Kaufmann, 2001.

[**SSP02**] Sushmita Mitra, Sankar K. Pal, Pabitra Mitra, *Data Mining in Soft Computing Framework: A Survey*, IEEE Transactions On Neural Networks, VOL. 13, NO. 1, January 2002

[**YPXS03**] Yingjiu Li, Peng Ning, X. Sean Wang, Sushil Jajodia R: *Discovering calendar- based temporal association rules*, Data & Knowledge Engineering volume 4, Elesvier publisher, Volume 44 pp- 193-214 , 2003

[FFM03] Feng Tao, Fionn Murtagh, Mohsen Farid: *Weighted Association Rule Mining using Weighted Support and Significance Framework*, International Conference on Knowledge Discovery and Data Mining, Proceedings of ninth ACM SIGKDD, pp 661-666, 2003.

[**YHB04**] Yao, Hong, Hamilton, H., and Butz, C. J. *A Foundational Approach to Mining Itemset Utilities from Databases*. Proceedings of the Third SIAM International Conference on Data Mining, Orlando, Florida, pp. 482-486, 2004.

[**TR04**] Timothy J. Ross, a book on "*Fuzzy Logic with Engineering Applications*", McGraw Hill International Editions, 2004.

[FAR04] Francisco Guil1, Alfonso Bosch, and Roque Mar´ın, *TSET: An Algorithm For Mining Frequent Temporal Patterns*, 15th European Conference on Machine Learning (ECML) and The 8th European Conference on Principles and Practice of Knowledge Discovery in Databases (PKDD), 20-24 September, 2004

[**YWA05**] Ying Liu, Wei-keng Liao, Alok Choudhary, *A Two-Phase Algorithm for Fast Discovery of High Utility Itemsets*, PAKDD 2005, LNAI 3518, Springer-Verlag Berlin Heidelberg, pp. 689 - 695, 2005.

[**ZTLJ05**] Zhai Liang, Tang Xinming, Li Lin, Jiang Wenliang, *Temporal Association Rule Mining based on T-Apriori Algorithm and its typical application*, Proceedings of International Symposium on Spatio-temporal Modeling, Spatial Reasoning, Analysis, Data Mining and Data Fusion, 2005.

[**OK05**] O.P. Vyas , Keshri Verma. *Temporal Association rule without candidate generation*, International Conference on Multilingual Computing and Information Management in Networked Digital Environment, Caliber, pp 113-119, 2005.

[**OKR05**] O.P.Vyas , Keshri Verma, Ranjana Vyas. *Temporal Approach to Association Rule Mining Using T-tree and P-tree*, LNAI 3587, pp. 651 – 659, Springer-Verlag Berlin Heidelberg, 2005

[**KO05**] Keshri Verma, O. P. Vyas, *Efficient calendar based temporal association rule*, SIGMOD Record, Vol. 34, No. 3, Sept., 2005.

[**AV06**] Ashish Mangalampalli, Vikram Pudi, *Fuzzy Logic-based Pre-processing for Fuzzy Association Rule Mining* [SSA06] K.P. Soman, Shyam Diwakar, V. Ajay, a book on "*Insight into Data Mining:Theory and Practice*", PHI Learning Private Limited, 2006.

[**AP06**] Arun K. Pujari, a book on "*Data Mining Techniques*", Universities Press, 2006.

[**YH06**] Yao, H. and Hamilton, H, J, *Mining Itemset Utilities from Transaction Databases, Data and Knowledge Engineering*, Volume 59(Issue 3), pp. 603-626, 2006.

[**MSZC06**] Maybin Muyeba, M. Sulaiman Khan, Zrrar Malik, Christos Tjortjis, *Towards Healthy Association Rule Mining HARM: A Fuzzy Quantitative Approach*, Springer, pp 1014-1022, IDEAL Spain 2006.

[**JW06**] Junheng-Huang, Wang-We, *Efficient Algorithm for Mining Temporal Association Rule*, IJCSNS International Journal of Computer Science and Network Security, VOL.7, No.4, April, 2007.

[**NS07**] Nicolas Turenne, Sylviane R. Schwer, *Temporal Representation for Gene Networks: towards a Qualitative Temporal Data Mining*, International Journal of Data Mining and Bioinformatics, 2007.

[**CVT08**] Chun-Jung Chu, Vincent S. Teng, Tyne Liang, *An Efficient algorithm for mining temporal high utility itemsets from data streams*, Science Direct, 2007, The Journal of Systems and Software, Vol. 81,No. 7, pp 1105-1117, 2008.

[**SMF08**] M. Sulaiman Khan, Maybin Muyeba, Frans Coenen, *Weighted Association Rule Mining from Binary and Fuzzy data*, International Conference on Data Mining, Springer, pp 200-212, 2008.

[**SMF08**] M. Sulaiman Khan, Maybin Muyeba, Frans Coenen, *A Weighted Utility Framework for Mining Association Rules*, Second UKSIM, IEEE Explore, 2008.

[ZG08] Zuoliang Chen, Guoquing Chen, *Building an Associative Classifier based on Fuzzy Association Rules*, International Journal of Computational Intelligence Systems, 2008.

[SMF09] Frans Coenen, *Fuzzy Weighted Association Rule Mining with Weighted Support and Confidence Framework*, PAKDD Workshops, Springer, pp 62-74, 2009.

[RVON09] Ranjana Vyas, Vivek Ranga, O.P.Vyas, Anne Gutschmidt, *Exploring Temporal Associative Classifiers for Business Analytics*,accepted in I[st] International Conference on Advanced Data Analysis, Business Analytics and Intelligence, IIM, Ahmedabad to be held on 6[th]-7[th] June'09.

[**MM09**] Maybin Muyeba, A Theoretic-model for Itemset Utility Mining with Fuzzy and Temporal Features, (communicated) IDEAL 2009

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